New Technologies Require Advances in Hydrologic Data Assimilation

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Extensive amounts of hydrologically relevant remote sensing data are becoming available and require special capabilities for analysis and interpretation. For instance, land-surface temperature data have been available for many years, and satellite precipitation data are becoming available at ever-increasing space and time resolutions. In addition, a number of platforms provide snow and vegetation parameters of increasing sophistication, and satellite missions targeted at measuring near-surface soil moisture are expected before the end of the decade.

However, current hydrologic remote sensing analysis and interpretation tools may not be adequate due to little use of such data until recent years. This can be attributed to an emphasis on atmospheric rather than hydrologic remote sensing missions, a relative immaturity of retrieval algorithms for deriving hydrologic information from remote sensing observations, hydrologic models that are unsuitable for ingesting remote sensing information, and a limited understanding of the techniques to objectively improve and constrain hydrologic models by assimilating remote sensing data.

The development of hydrologic data assimilation techniques is still in its infancy. While significant progress has been made in advancing hydrologically relevant remote sensing and assimilation techniques through focused ground- and airborne field studies, this expertise has yet to be applied to satellite data. Moreover, only a few hydrologic models that can directly use remote sensing observations have been developed. Figure 1 demonstrates how satellite observations of near-surface soil moisture content may be used to constrain the hydrologic model prediction of soil moisture using state-of-the-art hydrologic data assimilation techniques and models. This example uses actual space-borne, near-surface soil moisture observations from a historic satellite record in a data assimilation framework, and highlights the potential benefit of maturing these techniques. However, quantifying the improvement in hydrologic model predictions from assimilation of remote sensing data requires targeted field campaigns, and such data are lacking for the historic satellite records.

Because of its importance and because of our increasing ability to observe relevant hydrologic information remotely, it is expected that the amount of hydrologic remote sensing data will grow exponentially over the next decade. However, its usefulness will be limited by our ability to integrate and analyze diverse hydrologic information using data assimilation methods. Quantifying hydrologic process variability will require innovative interpretation of potentially large hydrologic observation volumes due to disparities in observation type, scale, and error (Table 1). Variations in instrument type, placement, and calibration of both remote sensing and in-situ hydrologic observations must be quantified.

Clearly, the complexities of future hydrologic observation scenarios demand that we pursue methods to organize and comprehend this information. It is therefore suggested that a comprehensive hydrologic data assimilation framework will be a critical component of future hydrologic observation and modeling systems.

A Brief History of Hydrologic Data Assimilation

The idea of combining current and past data in an explicit dynamical model, using the model's prognostic equations to provide time continuity and dynamic coupling amongst the fields, has evolved into a family of techniques known as data assimilation. In essence, data assimilation merges a range of diverse data fields with a model prediction to find the model representation that is most consistent with the observations. That best estimate can then be used to analyze hydrological processes or initialize a model forecast more accurately.

Data assimilation techniques were pioneered by meteorologists and have been used very successfully to improve operational weather forecasts for decades. Data assimilation has also been widely used in oceanography to improve ocean dynamics prediction. However, hydrologic data assimilation is still in its infancy. Fortunately, we have been able to jump-start hydrologic data assimilation by building on knowledge derived from the meteorologic and oceanographic data assimilation experience, with significant advancements being made over the past 5–10 years (e.g., review by *McLaughlin* [2002]).

Most techniques currently used to assimilate environmental data are based on 'variational' or 'Kalman filter' techniques. Variational techniques find the best fit between the forecast model state and the observations by minimizing an objective function over space and time. To minimize the objective function over time, an assimilation time "window" is defined and an adjoint model is typically used to find the derivatives of the objective function with respect to the model states. While an adjoint is not strictly required, it makes the problem computationally tractable. Alternatively, the Kalman filter sequentially updates the model forecast using the relative observation and model variances whenever observations become available.

The variational technique can be formulated with a 'strong constraint' where the model is assumed perfect, or a 'weak constraint' where errors in the model formulation are taken into account as process noise. The Kalman filter can be formulated as: direct insertion, which assumes perfect observations, ignores forecast information, and assumes zero correlation between the observations and other model states; nudging, where the weighting factor between the model forecast and the observations, commonly known as the Kalman gain, is empirically derived; optimal or statistical interpolation, where the Kalman gain is derived from assumed and typically time-invariant error co-variances; the extended Kalman filter, where error co-variances are propagated in time using a linearized or simplified forecast model; or the ensemble Kalman filter, where dynamic co-variances are derived from an ensemble of forecasts.

Variational methods are well suited for smoothing problems, but provide information on estimation accuracy only at considerable computational cost. Unfortunately, adjoints are not available for existing hydrologic models, and the development of robust adjoint models is difficult due to the nonlinear nature of hydrologic processes. While direct insertion, nudging, and optimal interpolation are computationally efficient and easy to implement, the updates do not account for system dynamics or measurement statistics, and information on estimation accuracy is limited.

The extended Kalman filter, while computationally demanding in its pure form, can be adapted for near-real-time application and

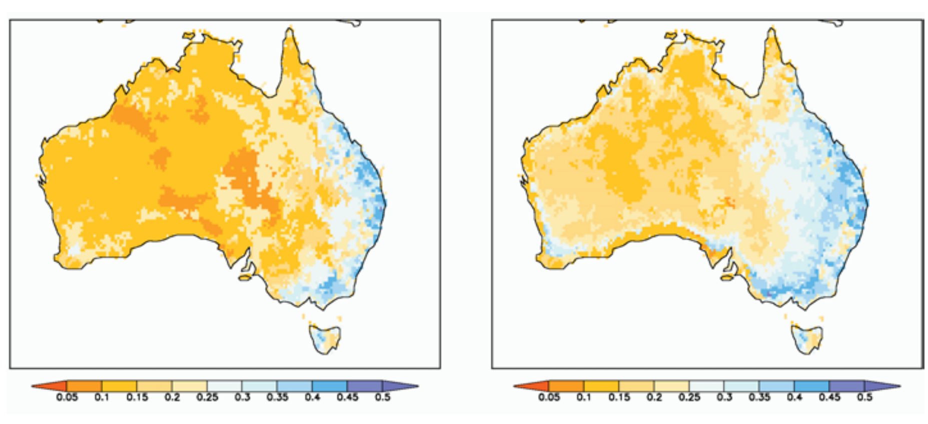

Fig. 1. Satellite observations of near-surface soil moisture content made by the scanning multifrequency microwave radiometer (SMMR) may be used to constrain hydrologic model predictions of soil moisture throughout the soil profile using data assimilation.

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provides information on estimation accuracy. However, it has only limited capability for dealing with model errors, and necessary linearization approximations can lead to unstable solutions. The ensemble Kalman filter, while it can be computationally demanding (depending on the size of the ensemble), is well suited for near-real-time applications, is robust, very flexible, and easy to use, and is able to accommodate a wide range of model error descriptions.

Examples of Hydrologic Data Assimilation

Data assimilation helps to maximize an observation's usefulness by not only propagating its information in space (horizontally and vertically) and time, but also by acting as an effective downscaling tool. Hydrological data assimilation systems that include higher resolution meteorological, land cover, and soil texture information can be constrained to lower resolution observations, such as passive microwave soil moisture. Additional resolution improvements may also be gained from the deconvolution of overlapping and multi-angle observations.

Because of snow's high albedo, thermal properties, feedback to the atmosphere, and its capacity for medium-term water storage, improved snow state estimation has the potential to greatly increase climatological and hydrological prediction accuracy. By assimilating snow water equivalent observations from remote sensing satellites, it has been shown that unobserved snow states, including snow depth and snow temperature, can be retrieved, and the prediction of runoff and atmospheric fluxes substantially improved.

Land surface skin temperature, which is a principal control on land-atmosphere fluxes of water and energy, is closely related to soil water states and is easily observable from space and aircraft infrared sensors in cloud-free conditions. However, skin temperature has a very short memory—on the order of minutes—due to the very small heat storage it represents. Therefore, correlations of skin temperature with other longer-memory states (that is, deeper temperature or moisture) must be exploited by the assimilation procedure to impact the model's long-term trajectory.

Table 1. Hydrologic Observations Available During the Next Decade.

Hydrologic Quantity	Remote-Sensing Technique	Time Scale	Space Scale	Accuracy Considerations
Precipitation	Thermal infrared	1 hour 1 day 15 days	4 km 1 km 60 m	Tropical convective clouds only
	Passive microwave	3 hours	10 km	Land calibration problems
	Active microwave	30 days	10 m	Land calibration problems
Surface soil moisture	Passive microwave	1-3 days	25-50 km	Limited to sparse vegetation, low topographic relief
	Active microwave	3 days 30 days	3 km 10 m	Significant noise from vegetation and roughness
Surface skin temperature	Thermal infrared	1 hour 1 day 15 days	4 km 1 km 60 m	Soil/vegetation average, cloud contamination
Snow cover	Visible/thermal infrared	1 hour 1 day 15 days	4 km 500 m-1 km 30-60 m	Cloud contamination, vegetation masking, bright soil problems
Snow water equivalent	Passive microwave	1-3 days	10 km	Limited depth penetration
	Active microwave	30 days	10 m	
Water level/velocity	Laser	10 days		Cloud penetration problems
	Radar	30 days		
Total water storage changes	Gravity changes	30 days	1000 km	Bulk water storage change
Evaporation	Thermal infrared	1 hour 1 day 15 days	4 km 1 km 60 m	Significant assumptions

Advances, Current Priorities, and Challenges in Hydrologic Data Assimilation

The application of data assimilation in hydrology has so far been limited mostly to one-dimensional, largely theoretical studies that assimilate near-surface soil moisture, soil skin temperature, or snow observations. Nevertheless, the feasibility of undertaking spatially distributed data assimilation in hydrological models has been demonstrated by a number of recent studies [e.g., *Houser et al.*, 1998; *Reichle et al.*, 2002; *Walker et al.*, 2002; *Crow and Wood*, 2003], and was the topic of the recent Catchment-scale Hydrological Modeling and Data Assimilation Workshop [*Troch et al.*, 2003].

With hydrologic data assimilation still in its infancy, there are many open areas of research. One key question is whether the land surface should be considered in isolation from or coupled to the atmosphere. If a coupled model is not used, then assimilation of land surface states can cause biases to arise in the fluxes back to the atmosphere. From a weather and climate forecasting perspective, it is the fluxes that are of most importance, while for agriculture and flood forecasting, the land surface states themselves are of primary importance.

A second key topic is the choice of assimilation technique. Though all of the assimilation techniques described above can theoretically be applied to almost any dynamic problem in the geosciences, an important factor in determining the choice of method is computational feasibility. As higher resolution observations from an increasing number of sensors become available, higher resolution models are developed, and near-real-time information is required, there is a clear trade-off against the computational requirements of the data assimilation technique and optimal use of the data.

We must also recognize that assimilation does not always improve model predictions. Accurate model and observation error statistics are required for successful data assimilation. If, for example, surface soil moisture observations are biased, information may be improperly propagated to depth. In the presence of biased near-surface meteorological forcing, assimilation of unbiased observations into a hydrological model can cause biased subsurface state estimates or land surface boundary conditions that are inconsistent with the overlying atmosphere, which can lead to degraded, and even unrealistic, surface flux predictions. However, a bias correction scheme can be implemented to correct for long-term model biases. Moreover, the increasing data stream from satellite platforms must be used to quantify model and observation error statistics more accurately.

Apart from the sheer volume of data that will be collected, there will be a disparity of scales and data types, all of which provide a piece of information about the state of the land surface that requires interpretation, though none provides the complete picture. It is clear that a comprehensive hydrologic data assimilation framework will be critical to integrate and analyze the extensive and diverse remote sensing data that will be available in the near future.

References

Crow, W., and E. F. Wood, The assimilation of remotely sensed soil brightness temperature imagery into a land surface model using ensemble filtering: A case study based on ESTAR measurements during SGP97, *Adv. Water Resour., 26*, 137–149, 2003.

Houser, P. R., W. J. Shuttleworth, H. V. Gupta, J. S. Famiglietti, K. H. Syed, and D. C. Goodrich, Integration of soil moisture remote sensing and hydrologic modeling using data assimilation, *Water Resour. Res., 34*, 3405–3420, 1998.

McLaughlin, D., An integrated approach to hydrologic data assimilation: Interpolation, smoothing, and forecasting, *Adv. Water Resour., 25*, 1275–1286, 2002.

Reichle, R. H., D. B. McLaughlin, and D. Entekhabi, Hydrologic data assimilation with the ensemble Kalman filter, *Mon. Weath. Rev., 130*, 103–114, 2002.

Troch, P. A., C. Paniconi, and D. B. McLaughlin, Catchment-scale hydrological modeling and data assimilation, *Adv. Water Resour., 26*, 131–217, 2003.

Walker, J. P., G. R. Willgoose, and J. D. Kalma, Three-dimensional soil moisture profile retrieval by assimilation of near surface measurements: Simplified Kalman filter covariance forecasting and field application, *Water Resour. Res., 38 (12)*, 1301, doi: 10.11029/2002/WRR001545, 2002.

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